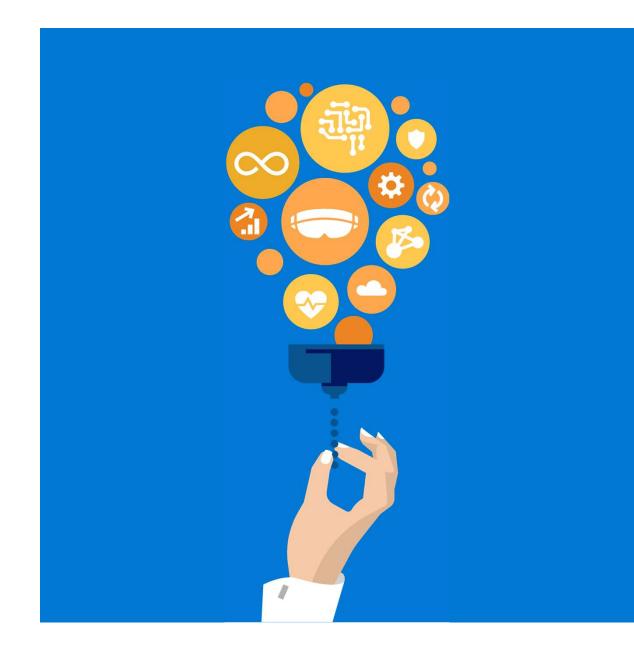


#### Deep Learning Vector Search Service

Jeffrey Zhu, Program Manager

OpML '19



#### **Evolution of Search**

Classic information retrieval is based on keyword matches and user behavior signals

- Query rewrite and other alteration techniques cannot enumerate all keyword expansions
- Insufficient user signals for tail queries

Novel search scenarios have emerged

 Natural language/Conversation, Question and Answer, image/multimedia

Vector search is a critical technique to improve search and enabling new scenarios

#### Traditional IR

**User Behavior** 

Knowledge models, Inverted index



Deep Learning and Vectorization

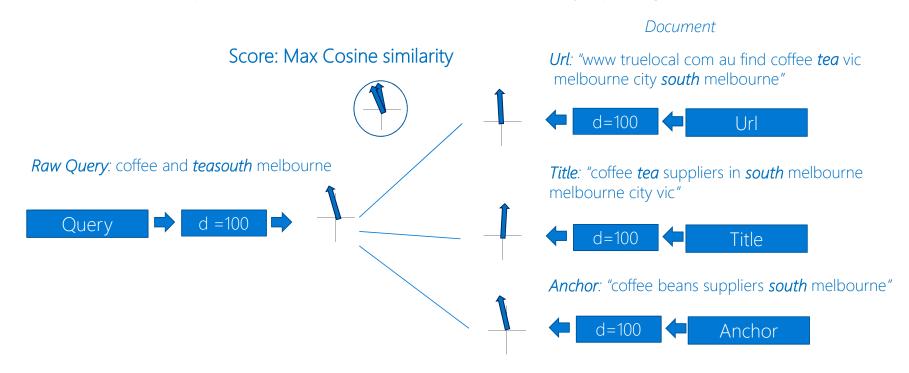
**DL** Based

Vectors and ANN

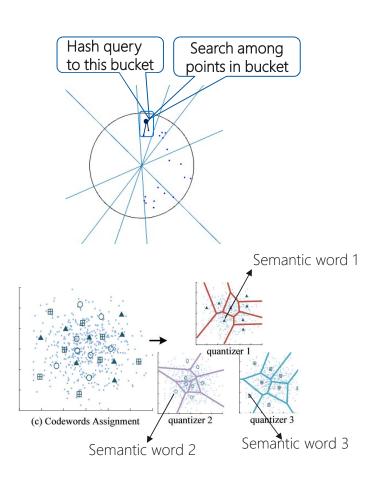
#### **Content Vectorization**

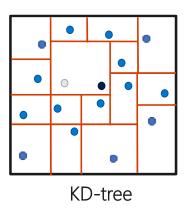
Use deep learning model to encode content as a vector

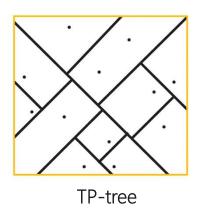
- · Distance between vectors represents semantic similarity
- · Better semantic representation, tolerant to out of vocabulary, spelling errors, connective words.

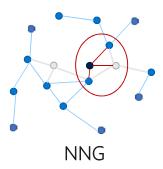


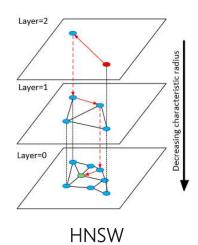
# **Vector Recall by Nearest Neighbor Search**



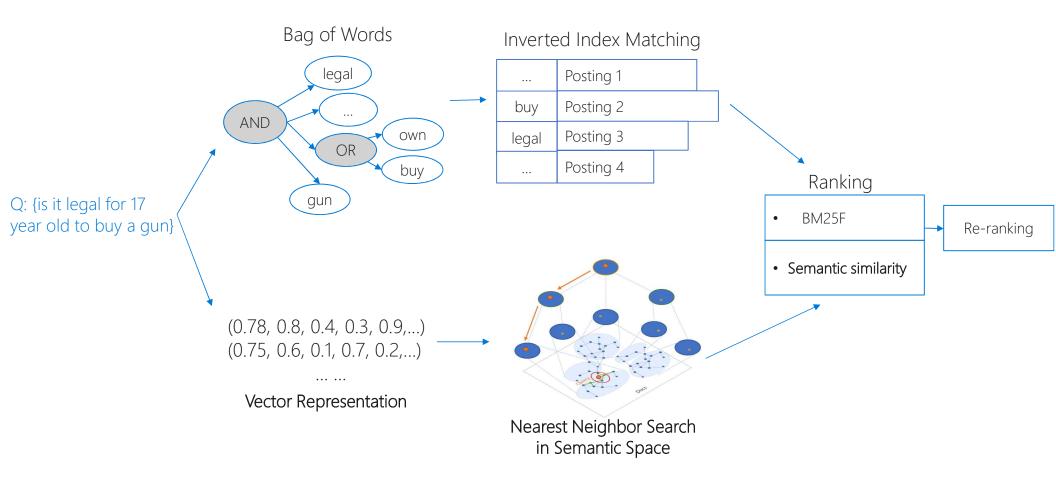








## From Keyword to Semantic Vector Search



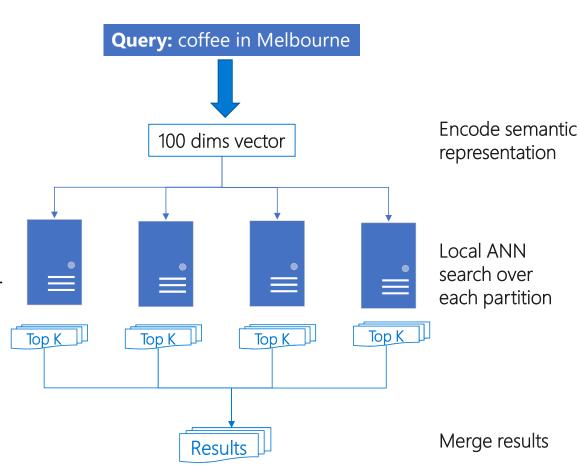
## SpaceV: Semantic Vector Search at Scale

- Better fidelity (NCG@infinity) than keyword search + BM25F ranker with the same document sets
- · Additional fidelity gain after combining with keyword search

L1 Fidelity on full index	Overall	Tail
Keyword + Vector Search	+3.24	+5.14

#### Deep Learning Vector Search Service

- Platform Capabilities
  - · Performance: <10ms search latency
  - · Scale: 100B+ vector index size
  - · Agile: Fast experimentation + deploy
  - · Flexible: Pluggable ANN algorithms
- Distributed serving
  - Randomly partition vectors into smaller vector indexes
  - Serving queries is distributed and aggregated before returning



## SpaceV: Semantic Vector Search at Scale

- High scale and Low latency
  - 40B+ vectors
  - Served with N (N=3) replica in 500+ servers
  - High capacity: 240M vectors per machines \* 1,800 QPS at most
  - · Low latency: 5ms in average and 8ms in 95%ile

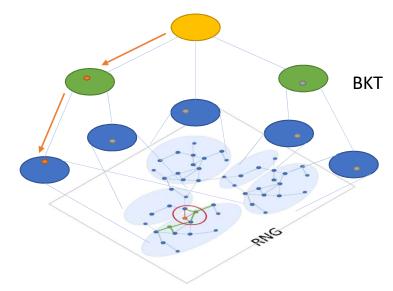
	QPS per replica	Avg latency (ms)	50% latency (ms)	95% latency (ms)
Normal Traffic	1,200	5.341	4.764	8.004
Peak Traffic	1,800	6.177	5.159	9.293

## **Key Innovations**

- · SPTAG Approximate Nearest Neighbor Algorithm
  - · Balanced k-means tree over relative neighbor graph
- Distributed Vector Index Serving
  - · K-means clustering for distributed serving
- Lower Cost Serving Hardware
  - · Offload index from memory to Solid State Disk (SSD)

## **SPTAG – Space Partition Tree and Graph**

- Hybrid approach to achieve high recall for both low and high dimension vectors
  - · BKT: Balanced K-means Tree
  - · RNG: Relative Neighbor Graph
- Designed for efficiency, scale, and agility
  - · Better trade-off between recall and latency
  - User customized distance
  - · Incremental update



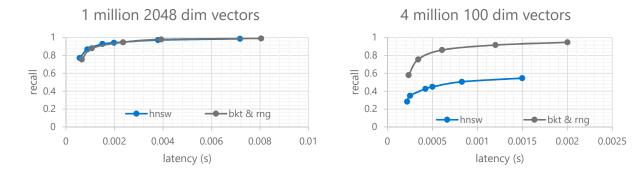
Balanced K-means Tree

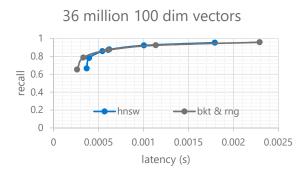
Object function:  $\min_{H,C} ||X - HC||_{\mathrm{F}}^2 + \lambda ||\mathbf{1}^\top H||_2^2$ 

Cluster chosen:  $k = \arg\min_{i} f(x_l, c_i) + \lambda s_i$ 

#### SPTAG – Space Partition Tree and Graph

- Evaluation
  - · Three datasets: 1M 2048 dim, 4M 100 dim, 36M 100 dim
  - · Two algorithms: HNSW, BKT & RNG

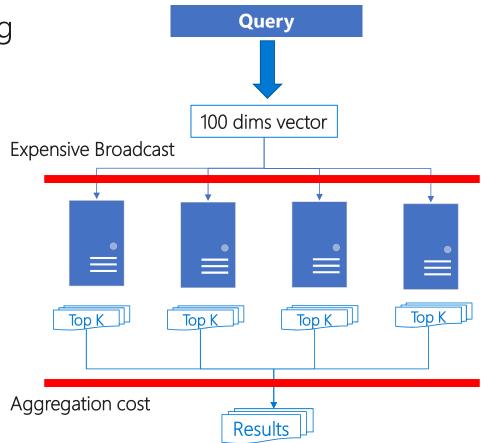




· Open source available at <a href="https://github.com/Microsoft/SPTAG">https://github.com/Microsoft/SPTAG</a>

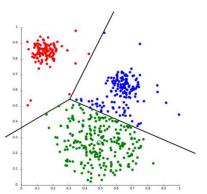
## **Distributed Vector Index Serving**

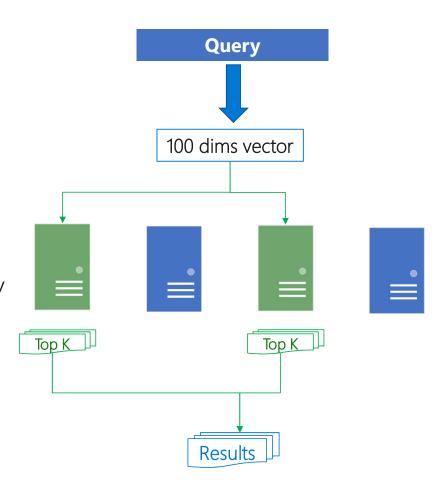
- · Challenges with Distributed Serving
  - Poor scalability
  - · Too much resource usage for each query
  - · Poor latency long tail



# **Distributed Vector Index Serving**

- Data partitioning with balanced kmeans clustering
  - · Each data partition maps to specific cluster
  - Each query is only sent to closest clusters (instead of global broadcast)
- Evaluation
  - Selecting top 5 out of 22 clusters can get the same recall as baseline, and only use 23% capacity





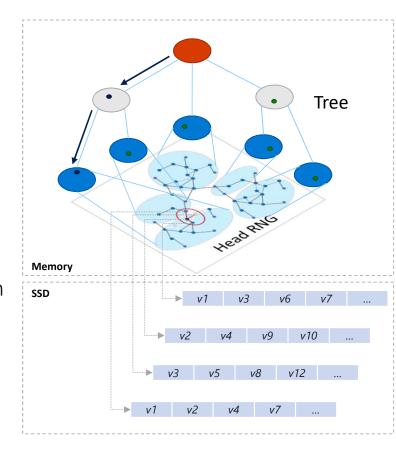
# **SSD Serving**

#### Challenges

- · Memory is bottleneck to lower cost serving
- Memory cache hit rate is low due to ANN random access pattern

#### ANN algorithm for SSD

- Build head index from partial vector and serve in memory
- Cluster tail vectors with head vectors as a center and serve in SSD



# **SSD Serving**

- Evaluation
  - · Dataset: 13 million 100 dim vectors
  - · 67% memory saving

	Index Size	Metadata Size	In Memory	In SSD
Memory Serving	32.3G	6.6G	32.3G	-
SSD Serving	47.5G	6.6G	6.6G	40.9G

	Average	99%	Recall
Memory Serving	1.05ms	1.32ms	0.962
SSD Serving	3.07ms	5.90ms	0.929

#### **Takeaways**

- Vector search is a critical technique to improve web search and power new capabilities such as question and answering, image search, etc.
- Key innovations in ANN algorithm and distributed vector index serving allows DLVS platform to serve high scale vector search scenarios (100B+ vectors)
- · Core ANN algorithm (SPTAG) is open source and available for developers to use
  - https://github.com/Microsoft/SPTAG